



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

Papers downloaded from AgEcon Search may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Adoption of Improved Sweetpotato Varieties in Ghana

Natson Eyram Amengor^{1*}, Bright Owusu-Asante¹, Kwadwo Adofo¹, Patricia Pinamang Acheampong¹, Benedicta Nsiah-Frimpong¹, Alex Nimo-Wiredu², Desmond Adogoba³, Joyce Haleegoah¹, Alex Adu-Appiah¹, Ernest Baafi¹ and Regina Sagoe¹

¹CSIR-Crops Research Institute, P.O.Box 3785, Kumasi, Ghana.

²International Institute of Tropical Agriculture (IITA), Av. FLM, via Corrane, Km 8. P.O.Box 709, Nampula, Mozambique.

³CSIR-Savanna Agricultural Research Institute, P.O.Box 52, Tamale, Ghana.

Authors' contributions

This work was carried out in collaboration between all authors. Authors NEA, BOA and KA designed the study, performed the statistical analysis, wrote the protocol and first draft of the manuscript. Authors PPA, BNF, ANW and DA managed the analyses of the study. Authors JH, AAA, EB and RS managed the literature searches. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJAEES/2018/39874

Editor(s):

(1) Mehmood Ali Noor, Chinese Academy of Agricultural Sciences, Institute of Crop Science, Key Laboratory of Crop Physiology and Ecology, Ministry of Agriculture, China.

Reviewers:

(1) Petro Maziku, College of Business Education, Tanzania.

(2) U. Barman, College of Agriculture, Assam Agricultural University, India.

Complete Peer review History: <http://www.sciedomain.org/review-history/23796>

Original Research Article

Received 27th December 2017

Accepted 2nd March 2018

Published 23rd March 2018

ABSTRACT

Aim: To examine the awareness and adoption of improved sweetpotato varieties in Ghana.

Study Design: Multi-stage sampling (Proportional Probability, Purposive and Random) of Sweetpotato farmers.

Place and Duration of Study: Improved Root and Tuber Technology Implementation Hubs. Fifteen (15) districts were selected. In each district, 5 communities and 35 sweetpotato farm households were selected from each district. The total sample size was 525 households across the country. The average treatment methodology was used to estimate the factors influencing awareness and adoption of improved sweetpotato varieties and the effect of awareness on adoption.

*Corresponding author: E-mail: eyramkwameamengor@gmail.com;

Results: Awareness of improved sweetpotato varieties are significantly influenced by household size, farm experience, number of plots cultivated and membership of FBOs. The population adoption rate was 67.2%, whereas the adoption rate within the subpopulation that is aware of the improved sweetpotato varieties was 69.6%. Potential adoption among the farmers who are not aware of the improved sweetpotato varieties was 59.3% hence resulting in an adoption gap of 13.8% due to incomplete awareness.

Conclusion: Dissemination efforts should include effective awareness creation about the improved sweetpotato varieties across the country for enhanced adoption. For effective promotion and adoption of improved sweetpotato varieties in Ghana, factors such as the age of the farmers, farm experience in sweetpotato cultivation, residential status and number of plots owned by farmers need to be considered in designing appropriate strategies.

Keywords: Food security; average treatment effect; exposure; parametric; adoption rates.

1. INTRODUCTION

Sweetpotato (*Ipomoea Batatas*) is an important local staple in Ghanaian due to its ability to address food security issues and serving as a source of income for various actors. Unlike previously, where production was mainly for subsistence, the crop has become a major source of employment for farmers in producing communities. For the same piece of land, the crop can be produced with less input requirements compared with others roots and tubers and helps in maintaining the fertility of the soil by serving as a cover crop and also the prevention of soil erosion [1].

Sweetpotato is consumed in a number of ways which is influenced by culture, location, and availability among others. For instance, it can be baked, boiled, served with meats, in soups, candied, in salads, desserts, cereals, cakes, as well as for making various cold and alcoholic beverages [2,3]. In Africa, both the roots and the leaves are consumed. In parts of East Africa, the tubers are sometimes sliced and sun-dried to produce chips, which are later ground into flour [4].

Sweetpotato is principally grown in farming systems in Sub Saharan Africa where food crop production is dominated by root crops. It is early maturing (about 3 months) and this has implications for food security. However, the roots are bulky and perishable unless properly cured hence, limiting the distance over which the roots can be economically transported. The production systems are highly influenced by climatic conditions which impact on the seasonality of the production and subsequently, on the quantity and quality of roots in markets, and high price fluctuations. In addition, there is minimal

processing of the roots both at the household and industrial levels. To address these challenges, there is the need to strengthen and improve the sweetpotato value chain (Commodity actors from input suppliers to producers/farmers, traders processors and consumers).

The main objective of this study is to understand the level of awareness of the improved sweetpotato varieties. Furthermore, it examines the determinants of the rates and intensities of adoption of improved sweetpotato variety/technologies.

2. METHODOLOGY

2.1 Study Area and Sampling Procedure

The study was conducted in 15 districts across Ghana. The study used a proportional probability sampling technique to select the districts focused on the intensity of sweetpotato area cultivated and production. The districts cultivating sweetpotato at a minimum total area of 2000 ha and 5000 tonnes minimum production were selected. The selection of the districts was also based on whether the West Africa Agricultural Productivity Programme (WAAPP) and/or Root and Tuber Improvement and Marketing Programme (RTIMP) had conducted demonstrations in the districts from 2011 to 2014. Multistage sampling technique was employed to sample the population for the study which involved purposive and random sampling techniques. Firstly regions were purposively sampled, secondly districts were purposively selected and thirdly communities were randomly selected. The sampling units were also randomly selected; in that, all sweetpotato farmers in the communities were listed, seven farmers were

selected from the list at random. These techniques were employed in order to capture sweetpotato technologies intervention districts and communities. To increase percentage coverage and statistical accuracy and validity, selection of households was spread out to cover many districts and communities. A total of 15 districts across the country were visited. In each district, 5 communities and 35 sweetpotato farm households were selected making a total of 525 farm households nationwide.

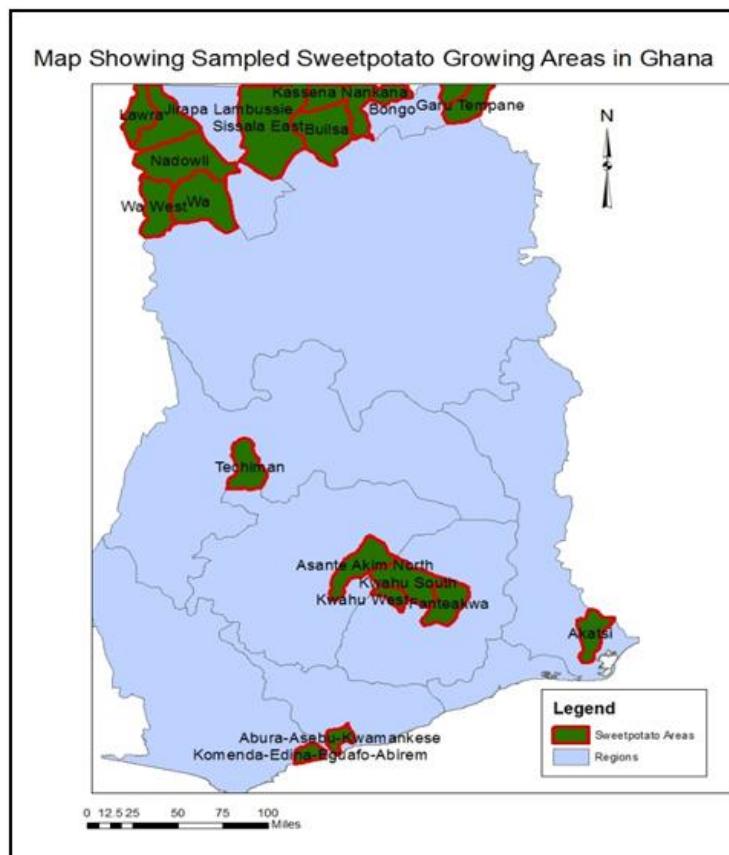
2.2 Data Collection and Data Analysis

Data was collected through a formal survey by the use of structured questionnaires administered to sampled households. Prior to the survey, the questionnaire was pre-tested in non-sampled communities. Information obtained included socio-demographic information, land use, awareness and adoption of improved sweetpotato varieties. Data were cleaned, organized and analyzed using STATA software version 14.

Descriptive statistics were used to summarize the variables of interest mainly at three levels, that is, at the regional levels, agro-ecologies and/or by gender of the household head. Inferential analyses such as simple regression and ordered logit/probit models were used to evaluate the causal interdependence between adoptions of improved sweetpotato technologies using the Average Treatment Effect (ATE) framework.

2.3 Analytical Framework

The exposure status to the Improved Sweetpotato Variety (ISV) for the i -th farmer in the population is defined by aw_i which has value 1 (or 0) if the farmer is (or is not) not aware of the ISV. Hence, the number of farmers who are aware is denoted by $N_{aw} = \sum_{i=1}^N aw_i$, where N is the total number of farmers in the population involved. Consequently, the awareness rate



Map 1.

(aw) for the ISV is defined as the percentage of farmers who are aware of the total population, given by:

$$aw = \frac{N_{aw}}{N} \times 100. \quad (1)$$

We define *adoption* as the cultivation of an ISV. A farmer is said to adopt if the farmer cultivates at least one of the improved sweetpotato varieties involved. Accordingly, the adoption rate (ad) is defined as the percentage of farmers who adopted the ISV, hence given by:

$$ad = \frac{N_{ad}}{N} \times 100 \quad (2)$$

where N_{ad} represents the number of farmers in the population who adopted a ISV.

In this paper, we apply the ATE estimation procedure proposed by Diagne and Demont [5], to obtain consistent estimates of the determinants of population adoption rates of improved sweetpotato varieties in Ghana. This approach is appropriate because although a number of improved sweetpotato varieties have been released in Ghana, not all the farmers seemed to be aware of these varieties. Furthermore, previous adoption studies have largely assumed that awareness of the technology is universal within the population. This may result in inconsistent estimates of the population adoption parameter [6,7], thus such estimates suffer from *exposure bias* and *selection bias* [5]. Rubin [8] proposed that the average treatment effect (ATE) parameter reflects the true population adoption rate and measures the impact of a “treatment” on a randomly selected person from the population treatment [9]. In this paper, the *treatment* refers to the farmer being aware of the improved sweetpotato varieties. Hence, farmers who are aware of the improved varieties are herein referred to as “*treated*” and those who are not aware are referred to as “*untreated*”. It follows that, the ATE is simply the mean population adoption outcome of awareness. In other words, it is the mean population adoption outcome when all members of the population are aware of the improved sweetpotato varieties [10]. The ATE measures the potential demand of the varieties by the farmers under complete awareness. The difference between the population means potential adoption and the population actual

(observed) adoption measures the *adoption gap*, which exists because the technology is not completely diffused within the population [5,10]. The average adoption rate within the subpopulation of treated (exposed) farmers is referred to as the average treatment effect on the treated (ATT), commonly denoted by ATE1. The population selection bias (PSB) refers to the mean difference between the population adoption rate (ATE) within the exposed subpopulation (ATE1) [5,9]. Subsequently, the population selection bias (PSB) which is the mean difference between the population adoption outcome (ATE) and the adoption rates within the subpopulation who are aware of the ISV (ATE1) [5].

Following [9,10], Rosenbaum and Rubin [11], let y_1 be the potential adoption outcome of a farmer who is aware of improved sweetpotato varieties and y_0 be the potential adoption outcome when not exposed to them. The “treatment effect” for the farmer i is measured by the difference $y_{1i} - y_{0i}$. Subsequently, the expected population adoption impact of exposure to the new varieties is given by the mean value $E(y_1 - y_0)$. As indicated by Diagne and Demont [5], exposure to a new variety is a necessary condition for its adoption implying that, farmers who are not exposed cannot adopt ($y_0 = 0$). The adoption impact of the i th farmer therefore is given by y_{1i} and the average adoption impact is given by $ATE = E y_1$.

To examine the impact of exposure on adoption of the ISV, let w be a binary variable that denotes awareness of the ISV where $w = 1$ if a farmer is aware of at least one improved sweetpotato variety and $w = 0$, if otherwise. The adoption rates and its determinants are estimated conditional on the observed covariates ((y_i , w_i , x_i , z_i), $i = 1, \dots, n$) of a randomly selected farmer from the population; where x_i is the vector of covariates that determines potential adoption rates (y_i) and z_i is the vector of covariates that determine awareness (w_i), with the possibility of x_i and z_i having some common elements.

The ATE methodology provides consistent estimates of true population adoption parameters by conditioning for observed awareness status. In this paper, the ATE is thus obtained using methods that depend on the validity of the conditional independence assumptions [9], which state that the awareness of the improved varieties, aw , is independent of the potential

outcomes, y_1 (adopt) and y_0 (not adopt), conditional on the observed set of covariates, z , that determine awareness of the improved varieties, aw .

This can be expressed as $P(y_i = 1 | aw, z) = P(y_i = 1 | z); i = 0, 1$.

The ATE parameters can be estimated from observed random vectors $(y_i, aw_i, x_i, z_i)_{i=1, \dots, n}$ through either a pure parametric regression based-methods where covariates are possibly interacted with treatment status variable (to account for heterogeneous impacts) or they are based on a two-stage estimation procedure where the conditional probability of treatment $P(aw = 1 | z) = P(z)$, called the propensity score, is estimated in the first stage and the ATE, ATE1 and ATE0 are estimated in the second stage by parametric or non-parametric methods [5].

In addition to the conditional independence assumption, it is assumed that potential adoption is independent from z , conditional on x : $P(y_1 = 1 | x, z) = P(y_1 = 1 | x)$. Thus the adoption rate and its determinants can be estimated from the sub sample that are aware, if the conditional independence assumption holds and if potential adoption is independent of vectors of determinants of awareness conditional on the vector of adoption determinants. Then the ATE (x) can be non-parametrically identified from the joint distribution of (y, z) condition on $w = 1$ given by:

$$ATE(x) = E(y | x, aw = 1) \quad (1)$$

This can be consistently estimated from a random sample of $y_i, x_i = 1, \dots, n$ drawn from only the subpopulation who are aware.

The parametric estimation procedure of ATE is based on the following equation that identifies

$ATE(x)$ and which holds under the conditional independence (CI) assumption [5]:

$$ATE(x) = E(y_1 | x) = E(y | x, aw = 1) \quad (2)$$

The parametric estimation proceeds by first specifying a parametric model for the conditional expectation on the right hand side of the second equality of equation (2) which involves the observed variables y, x and aw :

$$E(y | x, aw = 1) = g(x, \beta) \quad (3)$$

where g is a known (possibly nonlinear) function of the vector of covariates x and the unknown parameter vector β which is to be estimated using MLE procedures and the observations (y_i, x_i) from the subsample of exposed farmers only with y as the dependent variable and x the vector of explanatory variables. With an estimated

parameter " $\hat{\beta}$ ", the predicted values $\hat{g}(x_i, \hat{\beta})$ are computed for all the observations i in the overall sample and \hat{ATE} , $\hat{ATE1}$ and $\hat{ATE0}$ are obtained by taking the averages of the predicted $\hat{g}(x_i, \hat{\beta})$, $i = 1, \dots, n$ across the full sample (for \hat{ATE}) and respective subsamples (for $\hat{ATE1}$ and $\hat{ATE0}$):

$$\hat{ATE} = \frac{1}{n} \sum_{i=1}^n \hat{g}(x_i, \hat{\beta}) \quad (4)$$

$$\hat{ATE1} = \frac{1}{n_e} \sum_{i=1}^n aw_i \hat{g}(x_i, \hat{\beta}) \quad (5)$$

$$\hat{ATE0} = \frac{1}{n - n_e} \sum_i (1 - aw_i) \hat{g}(x_i, \hat{\beta}) \quad (6)$$

The effects of the determinants of adoption as measured by the K marginal effects of the K -dimensional vector of covariates x at a given point x are estimated as:

$$\frac{\partial E(y_1 | \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \quad k = 1, \dots, K \quad (7)$$

where x_k is the k -th component of x .

The ATE , $ATE1$, $ATE0$, the population adoption gap ($\hat{GAP} = \hat{ATE1} - \hat{ATE}$), and the population selection bias ($\hat{PSB} = \hat{ATE1} - \hat{ATE}$) parameters are estimated using the parametric regression based estimators (equations 4, 5, and 6).

It is essential to estimate the determinants of awareness because it provides information on the factors that are likely to influence a farmer to be aware of a new technology. However, these factors could either be the same or different from the determinants of adoption.

In estimating the parametric regression-based estimators, since y is a binary variable, equation 3 above is effectively a parametric probabilistic

model hence $E(y|x, aw=1) = P(y=1 | x, aw=1)$ are estimated using a logit model, $g(x, b) = \phi(xb)$. In this case, the parametric estimation of *ATE* reduces to a standard logit estimation restricted to the exposed sub-sample.

The marginal effects in equation (7) are also estimated using this *ATE* parametric model. Following and applying Stata add-on *adoption* commands, developed by Diagne and Demont [5], this paper employed appropriate estimators to consistently obtain the *ATE*, *ATE1*, *ATE0*, the population adoption gap, and the population selection bias.

2.4 Empirical Models

The awareness model

Following equation (1), the model for the determinants of exposure to ISV (aw_i) is explicitly expressed as:

$$\begin{aligned} Prob(aw_i=1|z) = P(z) = \psi(\alpha_0 + \sum_{k=1}^K \alpha_{H,k} H_{k,i} \\ + \sum_{k=1}^K \alpha_{X,k} X_{k,i} + \sum_{k=1}^K \alpha_{I,k} I_{k,i}) \end{aligned} \quad (8)$$

where aw_i is the binary response variables denoting awareness; ψ is the standard normal cumulative density function; $H_{k,i}$ is a set of covariates that represent the characteristics of the sampled households and their respective socioeconomic conditions; $X_{k,i}$ represents farm-level factors; $I_{k,i}$ denotes the set of institutional covariates.

The adoption model

Given that an ISV adopter refers to a farmer who cultivates IS varieties, following equation (3), the observed adoption incidence rate, ad_i , the probit model for the determinants of adoption of the IS varieties (ad_i) can be explicitly expressed as:

$$\begin{aligned} Prob(y_i=1|z) = P(z) = \psi(\alpha_0 + \sum_{k=1}^K \alpha_{H,k} H_{k,i} \\ + \sum_{k=1}^K \alpha_{X,k} X_{k,i} + \sum_{k=1}^K \alpha_{I,k} I_{k,i}) \end{aligned} \quad (9)$$

2.5 Definition of Variables and Expectations

To examine the determinants of awareness and adoption, of improved sweetpotato varieties, a number of explanatory variables were included in the logit model. These include household characteristics, farm-level factors and institutional factors.

The age of the household head is a continuous variable which could have a positive or negative effect on awareness and hence adoption. Older farmers have the tendency to be reluctant to adopting new technologies due to their past experiences, hence, are less likely to be aware and ultimately adopt improved sweetpotato varieties. The younger farmers, on the other hand, are more energetic and enthusiastic and willing to try new things, hence are more likely to be aware and adopt improved sweetpotato varieties. Education is expected to have a positive relationship with awareness and adoption of improved sweetpotato varieties. Farmers with more years of schooling are more likely to better understand the need for ways of improving farm output through the adoption of superior technologies and hence are likely to be aware and adopt such technologies.

Household size is likely to have positive effect on the awareness and adoption of improved sweetpotato varieties because of the elements of family labour which plays an important role especially when hired labour or mechanization is in inadequate supply or unavailable. Experience in sweetpotato cultivation is expected to have a positive effect on awareness and adoption. Residential status or being a native of the farming community is likely to have a positive relation on awareness and adoption. Nativity is perceived as a social capital because it guarantees access to communal production resources with less restriction hence, likely to enhance awareness and adoption of improved sweetpotato varieties [12].

Settler period for non-natives is expected to affect awareness and adoption positively or negatively. The longer the period, a settler is able to have almost equal access to production resources in the same way as a native. Number of plots and farm size are expected to have a positive effect on awareness and adoption. With larger farm sizes, farmers are likely to require more vines and hence likely to be aware and ultimately adopt improved sweetpotato varieties

Table 1. Expectation of variables that affect adoption of ISV

Variable	Definition	Expected sign
Age	Age of farmer in years	+/-
Education (years)	Education of farmer in years	+/-
Household size	Number of family members	+
Sweetpotato experience	Number of years in sweetpotato farming	+
Residential Status	Residential Status of farmer (1=Native, 0=Settler)	+
Settler Period	Period farmer settled in the study area	+/-
Plot No	Number of Plot owned by the farmer	+
Farm Size	Total farm in acres owed by the farmer	+
Household head	Respondent household head	+
Gender	1= Male; 0= Female	+
Marital Status	Marital Status of Farmer	+
FBO Membership	Membership in association	+
Farm Ownership	Whether the farmer owns land	+

Being a household head is expected to have a positive relation with awareness and adoption because household heads play an essential role in making production decisions which include the adoption of ISV. The gender variable is expected to have positive effect on awareness and adoption. Males are expected to have access to production resources such as land and labour as well as improved technologies. Marital status, FBO membership and farm ownership are expected to have positive effects on awareness and adoption.

3. RESULTS AND DISCUSSION

3.1 Socio-demographic Structure

Table 2 presents the summary of socio-demographic factors included in the model by adopter categories. In all, the age of the household head was averaged 46 years; however, it was about the same for adopters and non-adopters. Years of formal education averaged 5 years but adopters had a higher number of years than non-adopters. Adopters had a significantly smaller household size [9] than non-adopters [11] in comparison to the mean members per household across location. This might have an influence on the food sufficiency of the households depending on resource availability. In terms of sweetpotato farming experience, non-adopters are more experienced than adopters with a mean of 25 years of experience. This suggests that the less experienced is more likely to adopt the variety than the more experienced. Generally non-adopters had a higher percentage of natives than adopters with an overall mean of 66% of the respondent being natives. This has implications for access and ownership of resources such as

land. In terms of settlers, adopters had higher number of settling period than non-adopters. Adopters had a slightly higher number of farm plots than non-adopters with a mean farm size of 4 acres across location. With over 85% of farmers being household heads, across the study locations, more than 80% of both adopters and non-adopters were males. About 90% of respondents were married, but this proportion is higher among the adopters than non-adopters. The percentage of adopters belonging to farmer-based organizations was higher than that of non-adopters and this has an influence on the extent of awareness of the farmers to new technology. Across the locations, about 81% of farmers own the lands they were cultivating.

Commonly cultivated Improved Sweetpotato Varieties across the locations were Dadanyuie, Sauti, Santompona, Okumkom and Apomuden. Some farmers were growing improved sweetpotato varieties not knowing the approved names of these varieties. For example in Akatsi (Coastal Savanna), farmers were growing an improved variety they had named "shashango" and in Bawku (Guinea Savanna), there was another of such varieties called "Kuffour". Such varieties were grouped and the name "Agric Improved". Across the study area Santompona had the highest plot size (1.8 ha).

3.2 Awareness of Improved Sweetpotato Varieties

As indicated in figure 2, across the study area, about 95% of respondents were aware of the existence of Improved Sweetpotato Varieties (ISV). In the transition zone (100%) and coastal savanna (97.7%), almost all respondents were aware of ISV and though

lower than the others, the forest zone (84.2%) and guinea savanna (90.4%) had a very high level of ISV awareness. This in general terms is a good prospect for the adoption of the varieties in question. Knowledge on ISV was mostly acquired through colleague farmers (42.4%), agricultural extension agents (24.4%), demonstration plots (21.4%), media (8.6%) and researchers (3.2%). This suggests that agricultural information tends to diffuse quite faster through "farmer to farmer" and "extension to farmer" techniques. It is worth noting that these study areas are predominantly sweetpotato growing areas hence a lot of agricultural extension and research activities occur in these locations and this could enhance the level of awareness across location.

Diagne and Demont [5] empirically showed that sampled adoption rate is not a consistent estimator of the true population adoption rate if the technology is not universal among the population, consequently, such results suffer from "non-exposure" bias and it yields inconsistent and biased estimates of population adoption rates even when based on a randomly selected sample. Awareness, therefore, is a pre-requisite for adoption of agricultural technologies.

3.3 Factors affecting Awareness of Improved Sweetpotato Technologies

Table 2 presents the estimates of the factors affecting awareness of improved sweetpotato

technologies. The results show that major factors that influence awareness include household size, farming experience, number of plots owned, household head status and membership of a farmer-based organization.

Household size has a positive effect on awareness. This implies that large sized families were likely to be aware of improved sweetpotato technologies. The probability of a large family being aware of the ISV was higher than that of a small family.

Experience of the farmers had a negative effect on awareness. This implies that experienced farmers were less likely to be exposed as compared to less experienced farmers who were willing to try new varieties.

A number of plots owned by farmers had positive effects on awareness, implying that farmers with many plots were more likely to be aware of improved sweetpotato technologies than those with fewer plots. With the availability of plots, a farmer tends to search for more vines for planting and in the process is likely to become aware of improved varieties. Household heads are more likely to be exposed to improved sweetpotato technologies. Household heads make most of the farming decisions hence their influence on the decisions that borders on awareness of improved sweetpotato varieties are essential and are likely to become aware of improved varieties in their communities.

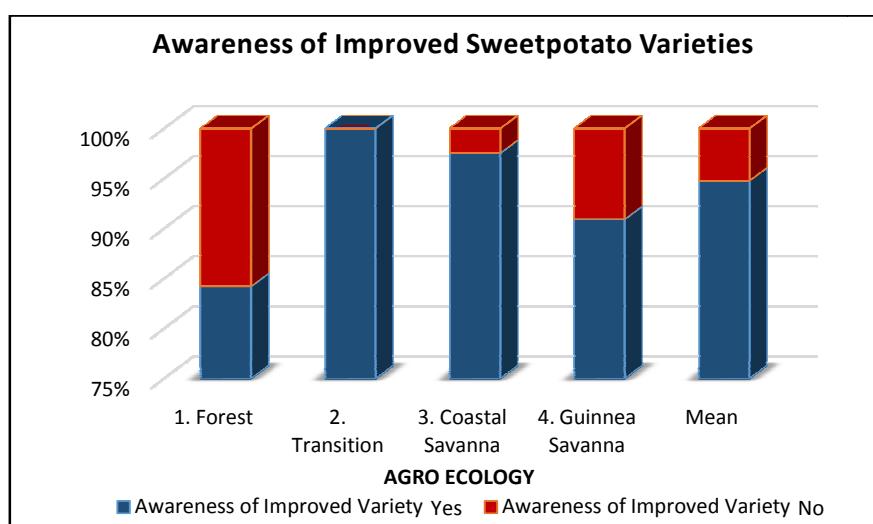


Fig. 2. Awareness of improved sweetpotato varieties

Table 2. Summary statistics of adopters and non-adopters of improved sweetpotato varieties

Variable	Description	Adopters (N=346)	Non-adopters (N=179)	All (N=525)	t stat
Age	Mean age of household head in years	45.92 (0.69)	45.19 (1.10)	45.68 (0.59)	0.579
Education (years)	Mean number of years in education	5.40 (0.29)	4.17 (0.38)	4.98 (0.24)	2.478***
Household size	Mean number of people in the household	7.71 (0.24)	9.74 (0.66)	8.41 (0.28)	3.469***
Sweetpotato experience	Mean years spent by the respondent in farming	24.47 (0.73)	25.77 (1.07)	24.92 (0.61)	1.018
Residential status	Is respondents residential status (1=Native, 0=Settler) (%)	64.8 (0.02)	77.8 (0.02)	65.7 (0.01)	1.978**
Settler period	Mean number of years respondents have stayed in area	6.33 (1.13)	1.39 (0.47)	4.05 (0.66)	3.812***
Plot no	Mean number of plots owned and cultivated by farmer	2.77 (0.08)	2.45 (0.07)	2.66 (0.06)	2.375***
Farm size	Mean farm size	3.89 (0.21)	4.51 (0.29)	4.12 (0.17)	1.712*
Household head	Is respondent household head (1=Yes, 0=No) (%)	85.2 (0.02)	87.8 (0.03)	86.1 (0.02)	0.809
Sex	Sex of respondent (1=Male, 0=Female) (%)	80.9 (0.02)	89 (0.02)	83.7 (0.02)	2.322**
Marital status	Marital status of respondent (1=Married, 0= Not married) (%)	91.5 (0.02)	86.6 (0.03)	89.8 (0.02)	0.561
FBO membership	Membership of a Farmer Based Organization (1=Yes, 0=Otherwise) (%)	64.2 (0.10)	52.3 (0.15)	60.2 (0.08)	2.657***
Farm ownership	Is farmland owned by respondent (1=Yes, 0=Otherwise) (%)	80.2 (0.04)	81.3 (0.06)	80.6 (0.03)	0.501

Table 3. Logit estimates of factors influencing awareness of improved sweetpotato varieties

Variables	Coefficient	Standard error
AgeHseHH	-0.002	0.012
EducYrs	-0.001	0.226
HsehSize	0.055***	0.198
FarmExp	-0.025**	0.013
ResidStat	0.828	0.540
SettlerPeriod	0.009	0.025
PlotNo	0.190*	0.103
FarmSiz	0.004	0.032
HseHH	0.674**	0.409
Gender	-0.176	0.483
MaritalStat	0.335	0.306
FBOMem	0.180***	0.052
FarmOwn	-0.062	0.146
Constant	0.177	2.094
N	240	
Pseudo R ²	0.181	

The asterisks, ***, ** and *, on the coefficients, denote that the coefficients are significant at the 1% and 5% and 10% levels, respectively

Farmers who belong to associations are likely to be aware of improved sweetpotato technologies. Most institution both extension and research interact more with farmer based organization with the aim of reaching out to many farmers within the shortest timeframe with improved technologies. Consequently, such farmers are likely to be exposed to ISV. This results are consistent with the findings of Nkamleu [13], who found that farmers learn about a technology from fellow farmers and other development agencies easily when they belong to farmer based organizations and such a medium ensures the faster dissemination of information.

During awareness creation on improved technologies, critical attention should be given to household size, farm experience, number of plots owned, household head status and membership of a farmer based organization.

3.4 Adoption of Improved Sweetpotato Varieties

In relation to sampled farmers who were aware of the existence of ISV, adoption as indicated in figure 3 was high in the Transition (100%), Coastal Savanna (90.8%) and Guinea Savanna (87.5%) as compared to mean adoption level of 79.1% across location. Adoption in the forest zone (6.2%) was however low due to the fact that few research and extension activities were sited in the said zone. Adoption of ISV was mainly

based on characteristics such as high yield (49.9%), good taste (24.4%) and early maturity (13.6%). There were other factors such as suitability for *ampesi*, weed control due to high canopy formation as well as disease/pest resistance.

Cultivated sweetpotato materials were primarily obtained from fellow farmers (60.8%), agricultural extension agents (30%) and researchers (9.2%). It re-emphasizes the fact that technology transfer is most effective through "farmer to farmer" modes compared to other means. This explains why the extension system uses key farmers as a point of contact in the dissemination of agricultural technology across study areas.

Non-adoption of ISV was highest in the forest zone (93.8%) over an average of 20.9% as indicated in figure 3. This was mainly because respondent alluded to the fact that ISV could not store for long periods (53.5%), susceptible to termite attack (34.6%), took longer to mature (8.7%) and did not have a good taste (2.8%). 90% of respondents were willing to adopt ISV if the above mentioned issues were addressed.

3.5 Logit Estimates of Factors Affecting Adoption of Improved Sweetpotato Technologies

Estimates of the factors influencing the adoption of improved sweetpotato technologies are presented in Table 3. The results indicate that, age of farmers, farm experience, residential status and number of plots owned by farmers are the key drivers of adoption across the study areas.

Age of farmer has a negative and significant effect on adoption of improved sweetpotato varieties. This depicts that older farmers are less likely to adopt improved technologies as compared to young farmers. Older farmers are risk averse and mostly content with whatever yields they get from their farms hence find it difficult to try new technologies for fear of losing the existing varieties that they inherited. Younger farmers on the other hand, are more enthusiastic and willing to explore new things including improved technologies. This results accords with that of Adesina, et al. [14], who found out that new agricultural technologies are more likely to be adopted by younger farmers because the youth are more likely to be risk takers and therefore try new innovations.

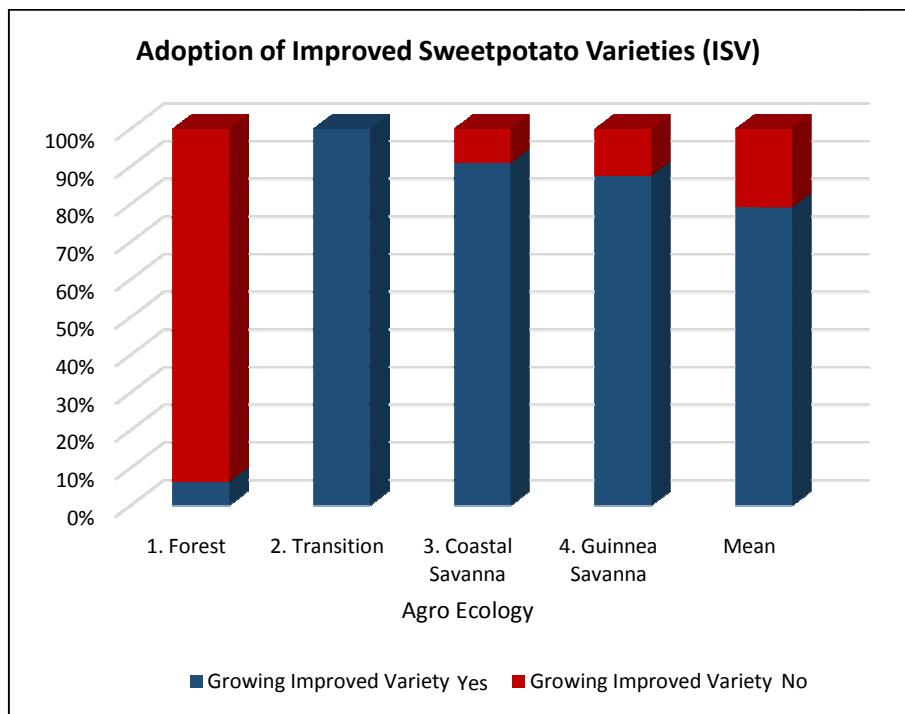


Fig. 3. Adoption of improved sweetpotato varieties

Farming experience also showed a negative relation to adoption of improved sweetpotato technologies. Most experienced farmers pride in their vast knowledge in the production of sweetpotato hence tend to be less likely to adopt improved technologies [15]. Less experienced farmers however, are open to new

ideas and are willing to try new method of production hence are likely to adopt improved sweetpotato technologies. This results corroborates with Gorfe [16], who found that the most efficient farmers appear to have less farming experience than the least efficient ones.

Table 4. Logit estimates of factors influencing adoption of improved sweetpotato varieties

Variables	Coefficient	Standard error
AgeHseHH	0.051	0.025
EducYrs	-0.034	0.041
HsehSize	-0.005	0.044
FarmExp	-0.052*	0.024
ResidStat	0.061**	0.060
SettlerPeriod	0.455	0.194
PlotNo	0.092**	0.073
FarmSiz	0.102	0.564
HseHH	1.011	0.877
Gender	-1.110	0.626
MaritalStat	1.959	1.082
FBOMem	-0.184	0.104
FarmOwn	-0.283	0.284
Constant	-4.764	3.886
N	240	
Pseudo R ²	0.169	

The asterisks, ***, ** and *, on the coefficients denote that the coefficients are significant at the 1% and 5% and 10% levels, respectively

Table 5. Adoption of improved sweetpotato varieties

Parameters	Global		Males		Females	
	Rates	Std. error	Rates	Std. error	Rates	Std. error
Ate	0.672***	0.034	0.667***	0.036	0.677***	0.226
ate1	0.696***	0.031	0.687***	0.033	0.687***	0.283
ate0	0.593***	0.060	0.606***	0.056	0.647***	0.092
Jea	0.533***	0.023	0.518***	0.025	0.519***	0.214
Gap	-0.138***	0.014	-0.149***	0.014	-0.159***	0.023
Psb	0.024	0.011	0.020	0.010	0.010	0.061
Number of observations	N = 240		N = 216			
Number of exposed	Ne = 184		Ne = 163			
Number of adopters	Na = 128		Na = 112			

Residential status has a significant positive effect on adoption of improved varieties. Natives have been in the communities for most of their farming lives hence, they are more likely to appreciate the benefits from improved varieties and are more likely to adopt improved sweetpotato varieties. This corresponds with Asante et al. [17] who found a positive significant relationship between adoption and nativity.

Number of plots owned by farmers also had a positive significant relationship with ISV adoption. Farmers who have many plots were likely to allocate plots for trying a new technology. Farmers with few plots tend to be satisfied with the available vines hence are less willing to allocate a portion of their land for trying new varieties and ultimately, less likely to adopt ISV.

3.6 ATE Estimation of Population Adoption Results

As shown in Table 4, adoption rate in the total population was 67.2%, whereas adoption rates among the farmer who were exposed were 69.6%. Adoption was therefore higher in the treated group than the population. If those who were not aware of ISV were made to be aware, their adoption rate would have been 59.3%. However, the observed adoption rates of ISV is 53.3%, which tends to underestimate the true population adoption incidence rates leading to an adoption gap of nearly 13.8% which would have been met if all sweetpotato farmers were aware of the improved varieties. Among the male population, average treated effect was 66.7% as compared to 67.7% in the female population. The male and female treated adoption rate was 68.7% which is higher than the global rate of the treated. Potential adoption among the untreated was 60.6% for males but 64.7% for females as indicated in Table 4.

4. CONCLUSION

This study examined the rates of awareness and adoption of improved sweetpotato varieties in across four agro-ecological zones of Ghana and examined factors influencing awareness and adoption. The results show that, awareness of improved sweetpotato varieties is significantly influenced by household size, experience, number of plots cultivated and membership of FBOs. To promote adoption of improved sweetpotato varieties in Ghana, factors such as the age of the farmers, farm experience in sweetpotato cultivation, residential status and number of plots owned by farmers need to be considered in designing appropriate strategies. Adoption rate in the total population was 67.2%, whereas among the treated it was 69.6%. Potential adoption of the untreated was 59.3% hence dissemination efforts should include effective awareness creation about the improved sweetpotato varieties across the country for enhanced adoption. To ensure a holistic improvement in the sweetpotato value chain and to enhance adoption, a conscious effort should be made by the Ministry of Food and Agriculture (MoFA) to project sweetpotato as an exportable crop; studying the marketing routes that exist will improve productivity in such areas and promote the crop's production. Agro-processing should be accelerated by introducing new value added products into the market. Sweetpotato processing should be improved from the traditional processing to a demand driven commercial system such as the production of sweetpotato composite flour which could be used as a substitute to wheat flour hence reducing the level of sugar needed as sweetener in baking. Extension services should make conscious efforts to disseminate outcomes of research programmes to farmers to keep them up to date with changing trends in sweetpotato production.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. PSDA. Promotion of Private Sector in Agriculture in Nairobi, Kenya 2. Adfoxx Kenya Ltd.; 2010. Available:www.gtzpsda.co.ke
2. Hand F, Cockerham K. The Sweetpotato. The McMillian Company New York; 1921.
3. Woolfe JA. Sweetpotato: An untapped food resource: Cambridge University Press; 1992.
4. Food and Agricultural Organisation. Nutrition country profile: Republic of Ghana. Ghana nutrition profile—nutrition and consumer protection Division. FAO. Rome; 2009.
5. Diagne A, Demont M. Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rates and their determinants. Agricultural Economics. 2007;37:201-10.
6. Geroski PA. Models of technology diffusion. Research policy 2000;29:603-25.
7. Kabunga NS, Dubois T, Qaim M. Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya. Agricultural Economics. 2012;43:473-86.
8. Rubin DB. Using propensity scores to help design observational studies: Application to the tobacco litigation. Health Services and Outcomes Research Methodology. 2001;2:169-88.
9. Wooldridge JM. Inverse probability weighted M-estimators for sample selection, attrition, and stratification. Portuguese Economic Journal. 2002; 1:117-39.
10. Simtowe F, Muange E, Munyua B, Diagne A. Technology awareness and adoption: The case of improved pigeon pea varieties in Kenya. Selected Paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil. 2012;18-24.
11. Rosenbaum PR, Rubin DB. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician. 1985;39:33-8.
12. Martey E, Wiredu AN, Etwire PM, Fosu M, Buah S, Bidzakin J, et al. Fertilizer adoption and use intensity among smallholder farmers in Northern Ghana: A case study of the AGRA soil health project. Sustainable Agriculture Research. 2013; 3:24.
13. Nkamleu GB. Modeling farmers' decisions on integrated soil nutrient management in sub-Saharan Africa: A multinomial Logit analysis in Cameroon. Advances in integrated soil fertility management in sub-Saharan Africa: Challenges and opportunities: Springer. 2007;891-904.
14. Adesina AA, Mbila D, Nkamleu GB, Endamana D. Econometric analysis of the determinants of adoption of alley farming by farmers in the forest zone of southwest Cameroon. Agriculture, Ecosystems & Environment. 2000;80:255-65.
15. Awotide BA, Diagne A, Omonona B. Impact of improved agricultural technology adoption on sustainable rice productivity and rural farmers' welfare in Nigeria: A Local Average Treatment Effect (LATE) Technique. African Economic Conference October; 2012.
16. Gofe HA. The comparative influence of intervening variables in the adoption behaviour of maize and dairy farmers in Shashemene and Debrezeit Ethiopia; 2007.
17. Asante BO, Villano RA, Battese GE. Integrated crop-livestock management practices, technical efficiency and technology ratios in extensive small-ruminant systems in Ghana. Livestock Science. 2017;201:58-69.

© 2018 Amengor et al.; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:

The peer review history for this paper can be accessed here:

<http://www.sciedomain.org/review-history/23796>